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Application of dynamic time warping to the recognition of mixed equipment activities in cycle time measurement

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ABSTRACT

Analyzing and measuring construction equipment operation are key tasks for managing construction projects. In monitoring construction equipment operation, the cycle-time provides fundamental information. Traditional cycle-time measurement methods have been limited by requiring significant efforts such as additional observers, time, and cost. Thus, this study investigates the feasibility of measuring cycle times by using inertial measurement units (IMUs) embedded in a smartphone. Because the mixed activities of construction equipment involve simultaneous actions of multiple parts, they cause low accuracy in equipment activity classification and cycle-time measurement. To enhance the recognition of these mixed activities and translate the results into reliable cycle time measurements, a dynamic time warping (DTW) algorithm was applied and the DTW distances of IMU signals were used as additional features in activity classification. To test its feasibility, data was collected on-site and the excavator's operation was recorded via IMUs embedded in a smartphone attached to a cabin. Using DTW, the suggested method achieved 91.83% accuracy for cycle-time measurement. This result demonstrates an opportunity to use operators' prevalent mobile devices to measure and report their equipment's cycle times in a cost-effective and continuous manner.

1. Introduction

Because construction equipment is a main component of construction production, systematically measuring and analyzing its operation is essential for monitoring project productivity. On construction sites, the cycle-time is crucial for measuring production rates since various construction activities are repetitive and the production rate generally depends on the number of cycles in a certain time [1]. For example, the production rate of earthmoving equipment (e.g., excavator, loader, truck) can be estimated directly from the multiplication of load volume (fixed specification) and cycle-time [2].

Measuring and analyzing equipment operations (including cycle-time measurement) has been largely conducted using manual methods such as: 1) analyzing production records using cost reports, unit rates, and schedules; 2) direct observation by managers; and 3) surveys and interviews of workers or operators [3,4]. Analyzing production records is generally not detailed enough because this method is designed for macro-level project management and is often slowly updated every week or two [3]. Direct observation is usually performed by field superintendents who track and control the progress of overall operations, but it is very time-consuming. Surveying and interviewing workers or operators [5] also require a considerable amount of time and resources [6,7]. To summarize, traditional methods that rely on manual efforts are error-prone, time-consuming, costly, and result in delayed information [8,9].

Such incompetency of manual methods has led to the adoption of automated data collection techniques using radio frequency identification (RFID) [10], global positioning systems (GPS) [11], computer vision [9], and laser detection and ranging (LADAR) [8]. Although automated data collection techniques have allowed us to monitor construction operations, limitations of cost (for attaching additional devices to equipment) and technological deficiencies (e.g., finite sensor range in RFID, obstructed line of sight in vision, difficulty in distinguishing stationary operations in GPS) may persist. An inertial measurement unit (IMU) may provide an alternative to addressing this issue since, during various operations, construction equipment may present different movements which are represented as different signals in IMU sensors [12]. In particular, the prevalence of smartphones that have embedded IMU sensors and wireless data communication capability offers an opportunity to use them in measuring and analyzing

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equipment operation in a continuous and cost-effective manner.

Thus, this study explores the feasibility of measuring cycle times of construction equipment using embedded IMU sensors in a smartphone. Its feasibility was investigated using data collected by an excavator, which is the most common equipment used in construction projects. This study begins with a literature review of existing work on techniques for activity classification, and using the IMU for activity classification. The following sections describe the details of the research objective and methodology, the conducted experiment, and the processes to analyze the data collected from the experiment for measuring a cycle time. The paper ends with a discussion of the results and potential applications of the findings.

2. Background

Because a cycle consists of repetitive activities, the cycle-time of construction equipment begins with activity recognition. Traditionally, activity recognition has been performed by human observers, which requires enormous manual effort. To address this problem, several research studies have focused on automated approaches which can be generally classified into vision techniques and sensor-based techniques. Vision techniques have been widely adopted in construction [13], with video recording commonly employed as a replacement for human observation. Although this method also requires extensive manual effort in the early stages of applying video recording methods [9], recent improvements in automated video interpretation have addressed this issue for advanced pattern recognition [14]. Several studies have applied an automated video interpretation in order to convert visual information to specific activities. For example, Zou and Kim [15] suggested a method to automatically quantify the idle time of hydraulic excavators using the hue, saturation, and value color space. Although the measured idle time can be used for monitoring and controlling daily (or hourly) operations, this information does not capture the cycle-time directly. To measure productivity information, Gong and Caldas [3] used video frames and a semantic layer with an operation process model to classify the states of activities (crane-bucket concrete pouring). Despite its strength and applicability, it remains challenging to continuously monitor multiple objects in the harsh construction environment (e.g., obstructed line of sight, moving backgrounds, and varying light conditions) [12,16].

Due to recent improvements and commercialization of numerous sensors, researchers have tried to utilize sensor-based approaches for productivity measurement in the construction domain. Oloufa et al. [17] explored the use of GPS (location and location changes) for tracking the situational awareness of construction equipment. Montaser and Moselhi [18] used RFID to measure the loading, traveling, and dumping cycle-time by calculating the time difference between a truck's entering and exiting times. These methods, suggested by diverse researchers, have similar rationales: the spatial-temporal data of equipment (pose or location) provides information that can be translated to working status according to pre-defined context-aware rules in the construction domain [3]. Although the previous methods provide reliable and accurate results, location-based methods are still incapable of tracking the stationary activities of construction equipment and providing a detailed analysis of production cycles [12].

To address the limitations of vision and location based approaches, this study focused on an IMU sensor. An IMU sensor is an electronic device that consists of an accelerometer, gyroscope, and magnetometer—generally all in tri-axial to get measurements in three different axes making a total of 9 degrees of freedom (DOF). The components of an IMU sensor (especially accelerometer and gyroscope) have been used for activity classification [19,20]. In the construction domain, IMUs have been utilized to collect activity data and classify different activities. Several studies have tried to classify activities such as masonry work [21,22] and iron work [23,24], and IMUs also have been used to monitor equipment operation. Ahn et al. [12,25] investigated the feasibility of measuring operation efficiency using accelerometer data for classifying excavator operations (i.e., engine-off, idle, and work). However, further decomposition of these activities was not explored. Mathur et al. [26] tried to measure cycle-time of an excavator operation using a smartphone, but they did not further examine the confusion among classes that frequently operate simultaneously. Akhavian and Behzadan [27] examined the utilization of built-in smartphone sensors to detect detailed construction equipment activities. Although this study classified activities (e.g., engine off, idle, scooping, moving, and dumping), the more detailed activity classification resulted in lower accuracy—three classes with 98.59% and four classes with 81.30% when using neural networks— which may not be useful for measuring cycle-times.

The basic underlying rationale of such applications is that every moving component or physical process involved in an equipment engine's operation produces its own movement signal. Therefore, signals created by the same operating engine have the same features under the same conditions [12]. In the case of an excavator's digging operation, the movement signal may have its own features that distinguish it from other operations. These applications represent the potential of cycle-time measurement through activity classification using IMU data collected from a smartphone.

3. Challenges and methodology

Although previous studies offered the potential for cycle-time measurement through activity classification using IMU, two main challenges remain: 1) combined signals from coinciding activities, and 2) determining a cycle's start and end times. First, several operational activities, such as wheel-based movement, cabin rotation, and bucket movement, can coincide. In this case, the signal collected from the IMU combines the three activities' signals. The mixed activity, defined as an activity involving simultaneous actions of multiple machine parts (e.g. excavator's arm, cabin, undercarriage), could cause misclassified activity in the sensor data, leading to inaccurate cycle-time measurements. Second, the mixed activity also makes it difficult to define the start and end times of a cycle. Although the mixed activities can be distinguished by using more classes (e.g., adding a new class as bucket/arm movement with anti-clockwise rotation), a greater number of classes may decrease the activity classification results [27].

To this end, this study aims to recognize the start and end times of equipment operation cycles, by harnessing signals captured by smartphones (equipped with IMU sensors) mounted inside the cabins of construction equipment. In addition, this study will translate them into cycle-time measurements and examine their accuracy in a real-world operation of an excavator.

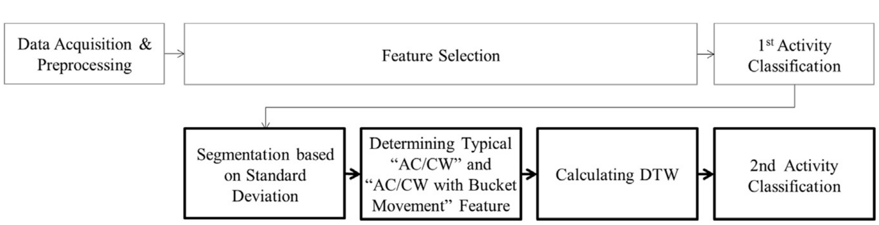

Fig. 1. Research procedure.